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Document Version
Publisher's PDF, also known as Version of record

Publication date:
2022

Link to publication in University of Groningen/UMCG research database

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Mixed-Effects Trait-State-Occasion Model: Studying the Psychometric Properties and the Person–Situation Interactions of Psychological Dynamics

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ABSTRACT

The trait-state-occasion model (TSO) is a popular model within the latent state-trait theory (LST). The TSO allows distinguishing the trait and the state components of the psychological constructs measured in longitudinal data, while also taking into account the carry-over effects between consecutive measurements. In the present study, we extend a multilevel version of the TSO model to allow for the combination of fixed and random situations, namely the mixed-effects TSO (ME-TSO). Hence, the ME-TSO model is a measurement model suitable to analyze intensive longitudinal data that allows studying the psychometric properties of the indicators per individual, the heterogeneity of psychological dynamics, and the person–situation interaction effects. We showcase how to use the model by analyzing the items of positive affect activation of the crowdsourcing study HowNutsAreTheDutch (HoeGekisNL).

Intensive longitudinal data are rich and complex data, which allow zooming in on the day-to-day life of individuals. This has brought great opportunities but also great challenges to researchers studying psychological dynamics (Hamaker et al., 2015; Hamaker & Wichers, 2017). With intensive longitudinal data, researchers can study in detail the stability and variability of the persons' attributes in short periods of time and how these attributes are related to each other over time. Furthermore, researchers can include time-invariant and time-varying covariates to fully explore how trait-like variables, situational variables, and situational circumstances have an effect on the dynamic process of interest. Yet, intensive longitudinal methods, such as ambulatory assessment (Trull & Ebner-Priemer, 2014, 2020) can also be a burden for the participants due to the frequency of the measurements and because answering the questionnaires can interfere with the activities and interactions in their daily life (Shiffman et al., 2008).

To keep the burden as low as possible, questionnaires tend to be short and in many situations one single question is used as a direct measure of the psychological attribute of interest (e.g., the network dynamics of symptoms, Bringmann et al., 2013). Nevertheless, in some cases researchers do use multiple items to measure one unique construct such as when measuring positive or negative affect (e.g., Geschwind et al., 2011; Snippe et al., 2015). In these cases, a common practice is to compute the sum scores and to study the dynamics of these scores. However, using sum scores can mask the underlying structure of the construct and lead to biased and unreliable results (Fried et al., 2016; McNeish & Wolf, 2020).

To tackle these issues, researchers can use measurement models for intensive longitudinal data. The most common measurement models used to analyze intensive longitudinal data are multilevel structural equation models (multilevel SEM; Geiser, 2020; Geiser et al., 2013; Roesch et al., 2010) and multilevel dynamic factor analysis (DFA; Fuller-Tyszkiewicz et al., 2017; Song & Zhang, 2014). On the one hand, multilevel SEMs are confirmatory factor models that separate the within-person (state) and the between-person (trait) components of the observed variables while accounting for measurement error. Some of these models such as the multistate-singletrait model are encompassed in the so-called latent state-trait theory (LST; Geiser, 2020; Steyer et al., 2015). In particular, the LST theory explicitly defines variance coefficients to study the psychometric properties of the observed indicators. These variance coefficients estimate the reliability of each indicator and to what extent the indicator is trait- or state-like (Steyer et al., 2015). A shortcoming of multilevel SEMs, however, is that these models estimate the parameters of interest in the whole sample ignoring the individual heterogeneity. In contrast, multilevel DFA models fully explore both inter- and intra-individual differences by allowing parameters to vary across individuals, while also including random autoregressive effects to study individual dynamics (Song & Zhang, 2014). Autoregressive effects are of key interest in intensive longitudinal data because they capture the influence of the variables on themselves over time. Note that multilevel DFA models also account for measurement error, hence, reliability estimates per individual have been proposed for these models (Fuller-Tyszkiewicz et al., 2017).

However, most applications of both multilevel SEM and DFA models have been mainly focussed on exploring the dynamic latent structure without taking into account time-invariant or time-varying covariates. As a consequence, little

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can be said about the person–situation interactions with these kind of models. In general, time-invariant covariates, also referred to as between-covariates, include trait-like variables such as neuroticism or optimism. In contrast, time-varying covariates, also known as within-covariates, include situational circumstances like being in a party or at work. Especially time-varying covariates can be of great relevance to understand psychological dynamics because they provide insight into the development of the dynamic process (McNeish & Hamaker, 2020; Ram & Gerstorf, 2009) as well as into the person–situation interactions (Geiser et al., 2015). In particular, Geiser et al. (2015) proposed an LST approach for the combination of random and fixed situations to study person–situation interactions, which includes characteristics of the situations as time-varying covariates.

In this paper, following Geiser et al. (2015), we introduce a comprehensive measurement model for intensive longitudinal data to study the person–situation interaction. This extension, which we call the mixed-effects trait-state-occasion model (ME-TSO), is fully encompassed within the dynamic structural equation modeling framework (DSEM; Asparouhov et al., 2017, 2018). More specifically, the ME-TSO is an extension of the trait-state-occasion model (TSO; Cole et al., 2005; Eid et al., 2017), which is an LST model (Steyer et al., 2015). In a nutshell, the ME-TSO model allows (a) distinguishing the trait and the state components of the variables, (b) studying individual dynamics by including random autoregressive effects, (c) analyzing the person–situation interactions by adding time-varying and time-invariant covariates, and (d) evaluating the psychometric properties of the items used in intensive longitudinal data.

The outline of this paper is as follows. We first provide a detailed review of the TSO model. Next, we introduce the ME-TSO model, which accounts for the person–situation interaction and the heterogeneity of the individuals. We also discuss the implications of this extension for the definition and computation of the variance coefficient components traditionally defined in the LST theory. Furthermore, we provide an empirical application of the ME-TSO model, in which we analyze the items of positive affect activation from the HowNutsAretheDutch crowdsourcing study (van der Krieke et al., 2017; van der Krieke et al., 2016). Lastly, we discuss the advantages and limitations of this new approach. Code to implement this model is available in the git repository https://github.com/secastroal/ME-TSO.

The trait-state-occasion model

The TSO model (Cole et al., 2005; Eid et al., 2017) is a model encompassed within the LST theory (Steyer et al., 1992, 2015). Initially, the TSO model was introduced and applied as a longitudinal SEM (e.g., Cole et al., 2009; Conway et al., 2018; Eid et al., 2017; Musci et al., 2016). This means that it has been presented as a single-level model, which requires the data to be in wide format (i.e., one row per subject and one column for each repeated measure). However, we have previously presented a multilevel version of the TSO model (Castro-Alvarez et al., 2021), the path diagram of which is shown in Figure 1. In contrast to the single-level TSO model, the multilevel TSO model requires the data in long format and is therefore more suitable to analyze intensive longitudinal data. Moreover, while
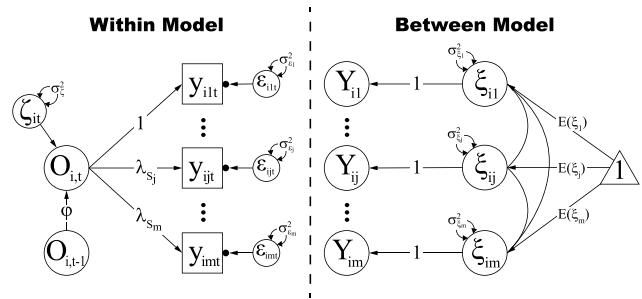
Figure 1. Path diagram of the multilevel TSO model. y_{ijt}: Observed scores of person i of the j-th indicator at time t. ε_{ijt}: Measurement error of person i of the j-th indicator at time t. $\sigma^2_{\varepsilon_j}$: Measurement error variance of the j-th indicator. $O_{i,t}$: Latent occasion-specific score of person i at time t. λ_{S_j}: Factor loading from $O_{i,t}$ on the j-th indicator variable. φ: Autoregressive effect between consecutive latent occasion-specific variables $O_{i,t-1}$ and $O_{i,t}$. $\zeta_{i,t}$: Latent occasion-specific residual of person i at time t. σ^2_ζ: Variance of the latent occasion-specific residual. ξ_{ij}: Latent trait score of person i of the j-th indicator. $E(\xi_j)$: Overall mean of the latent trait variable of the j-th indicator. $\sigma^2_{\xi_j}$: Variance of the latent trait variable of the j-th indicator. Furthermore, the dots at the end of the arrows in the within-level model represent the random intercepts of each indicator variable, which are then represented as the latent variables Y_{ij} in the between-level model. Random intercepts are commonly depicted as latent variables in SEM models due to the latent centering of the dependent variables.

the single-level TSO model allows testing for longitudinal measurement invariance (Meredith, 1993; Meredith & Teresi, 2006), the multilevel TSO model assumes that longitudinal measurement invariance holds. In other words, the multilevel TSO model assumes that the measurement of the construct of interest (e.g., positive affect) over time does not change. Lastly, the multilevel TSO model is easier to apply and estimate than the single-level TSO model because it has a smaller number of free parameters and it allows to easily handle many measurement occasions and missing data (Castro-Alvarez et al., 2021; Geiser, 2020; Geiser & Lockhart, 2012).

In a nutshell, the TSO model (both single-level and multi-level) acknowledges that psychological variables are not purely traits nor purely states but a combination of both (Cole et al., 2005; Eid et al., 2017). In addition to this, the TSO model accounts for the autoregressive structure likely to be found in longitudinal data. Hence, the TSO model can not only distinguish between the trait and the state components of the psychological variables of interest, but also accounts for the temporal effects from a previous occasion on the next occasion. In other words, autoregressive effects represent the tendency of persons to feel or behave as they were feeling or behaving just the moment before. For example, in case of a positive autoregressive effect, a person that starts their day with a relatively good mood will probably keep being in a good mood throughout the day. One key difference of the TSO model with other LST models is that the trait variables ξ_j represent the trait of the persons on the first measurement occasion and are not necessarily stable over time. This property is extensively explained in Eid et al. (2017).

Mixed-effects trait-state-occasion model

While the multilevel TSO model mentioned in the previous section is more suitable to analyze intensive longitudinal data than its single-level counterpart, it is still limited. Firstly, a clear

limitation of the TSO model is that it assumes that the different parameters of the model apply to the whole sample. This ignores one of the main principles of intensive longitudinal methods, which is the emphasis on the individual and individual heterogeneity. Considering the autoregressive effect, it is reasonable to expect that this effect will be different among multiple individuals (Kuppens et al., 2010; Nesselroade, 1991). For example, if we are measuring positive affect, persons that are very optimistic might have a higher autoregressive effect than persons that are more pessimistic. This may imply that a high positive effect at the beginning of the day will have a larger impact throughout the day even if something negative happens. On the other hand, persons that are more pessimistic might be more responsive to the different situations throughout the day. As a result, these persons' positive affect might vary more and they would be better described by a lower autoregressive effect on positive affect.

Secondly, another limitation of the TSO model is that the effects of the situation and the person–situation interaction are confounded in the latent occasion-specific residual term ζ_{it}. This means that the model cannot indicate if the variability in the construct of interest is due to specific situations. For example, consider a person who is struggling at work during a daily diary study on positive affect. Probably, the measurements of this person when they were at work will show lower levels of positive affect, in contrast to the measurements taken when they were not. As with most measurement models for intensive longitudinal data, these differences are currently not captured or modeled with the multilevel TSO model.

To overcome these limitations, we extended the multilevel TSO model within the DSEM framework (Asparouhov et al., 2017, 2018) in combination with the LST random and fixed situation approach (LST-RF) proposed by Geiser et al. (2015). First of all, DSEM is a framework that has been especially developed to analyze intensive longitudinal data. To account for the dynamics in the data, DSEM allows to easily include observed and latent lagged variables of any order (Hamaker et al., 2018). Furthermore, it also allows the within-level parameters such as regression coefficients, factor loadings, and residual variances to vary randomly across individuals. Note that all random parameters are then modeled as latent variables in the between-person level model. DSEM is fully implemented within the Bayesian framework in Mplus (Version 8.0 or newer, Muthén & Muthén, 2017) but fitting DSEM models in any other Bayesian software (e.g., JAGS, Stan) is also possible.

A first step into extending the TSO model is allowing the within-person parameters to vary randomly over the sample. The most flexible and unconstrained extension would be to allow the autoregressive effect φ, the factor loadings of the latent occasion-specific residual λ_S, and the variance of the latent occasion-specific residual σ_ζ^2 to vary across individuals. This means adding an i subscript to all of these parameters. However, such a complex DSEM model would require a large sample and long-time series to deliver reliable estimates (Schultzberg & Muthén, 2018), which are conditions that are rarely satisfied in intensive longitudinal psychological research (Vachon et al., 2019). To strike a balance between flexibility and practical feasibility, and based on the common statistical

techniques used to analyze intensive longitudinal data (Bringmann et al., 2013; Kuppens et al., 2010), we prioritize allowing the regression slopes and the autoregressive coefficients to vary randomly across individuals.

Additionally, to distinguish between the effect of the situation and the effect of the person–situation interaction, we consider the LST-RF approach (Geiser et al., 2015). This approach includes situational variables as dummy variables to identify *situation-specific traits, situation effects*, and *person–situation interaction effects*. The LST-RF approach assumes that the situations where the measurements take place can either be random or fixed depending on the study design and on the researcher's knowledge about the situations. In general, random situations are situations of which the specifics are unknown. This can happen by design. For example, in an ambulatory assessment study the measurements are collected at random situations throughout the duration of the study, while no information about the situation was collected. In contrast, fixed situations are situations of which information is available to the researcher. For example, in experimental designs, the situation in which the experiment takes place can be manipulated to create different conditions. Moreover, fixed situations can occur "naturally" if individuals had to report at the moment of measurement whether they were at home, at work, or at some other place (Geiser et al., 2015).

In particular, in intensive longitudinal studies, random and fixed situations can be combined into the design if details about the situation are collected. In this case, the repeated measurements are observed throughout the study across diverse random situations, which might share some characteristics (e.g., place or time of the day). These random situations that have something in common define a fixed situation that might be of interest in the research question. This means that the random situations are nested in a few fixed situations. For example, during an intensive longitudinal study, participants report their emotions across several days. Of course, the situations in which the measurements take place are very diverse, depending on where the participants were, with whom, if they were hungry, if they just did some exercise, etc. These are random situations. However, if they also report whether they were alone at the moment of measurement, then, we can group the random situations into two fixed situations: Being alone and not being alone. Collecting information about the situations where the measurements happen allows studying the impact of the situation on the behavior or attitudes of interest and the person–situation interaction (Geiser et al., 2015).

Here, we present how to extend the multilevel TSO within the DSEM framework and the LST-RF approach (see Figure 2), namely the mixed-effects TSO model (ME-TSO). The ME-TSO requires a set of indicators (i.e., item scores or sumscores) that measure the same psychological construct over time in an intensive longitudinal study. Consider, for example, an ambulatory assessment study where the participants report m positive emotions such as being cheerful or being enthusiastic multiple times a day for a couple of weeks (with $m \geq 2$). Let y_{ijt} be the observed score of person i on variable j at time t. For example, $y_{2,1,5}$ will be the observed score of the second person on the first emotion at the fifth time point of the ambulatory
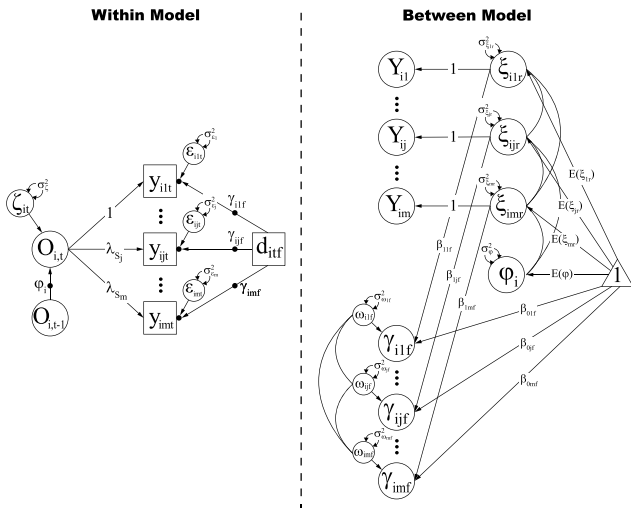
Figure 2. Path diagram of the ME-TSO model. In the within-level model, the dots at the end of an arrow represent the random intercepts and the dots on an arrow represent the random slopes and the random autoregressive effect. All these random effects are represented as latent variables in the between-level model.

assessment. To facilitate the presentation of the model, consider that the observed scores y_{ijt} are the responses to a set of items that measure positive affect, with $j = 1, 2, \ldots, m$. Now, let Y_{it} be an m-variate vector that encompasses the observed scores of the positive emotions of person i at time t, as follows:

$$Y_{it} = \begin{bmatrix} y_{i,1,t} \\ y_{i,2,t} \\ \vdots \\ y_{i,m,t} \end{bmatrix}. \tag{1}$$

Additionally, in the ME-TSO model, the situation under which the observations Y_{it} were collected matters, as it allows studying the person–situation interaction. Then, given $l + 1$ mutually exclusive fixed situations $s_0, s_1, \ldots, s_l$, one of the fixed situations is defined as the reference situation and the other l fixed situations are added as dummy variables to the model. Furthermore, as the model is encompassed within the LST theory (Steyer et al., 2015), it assumes that the observed scores of the positive emotions are measured with error. Hence, the measurement model of the ME-TSO model is defined as follows:

$$Y_{it} = \tau_{it} + \varepsilon_{it}, \tag{2}$$

where τ_{it} is a m-variate vector with the true scores of the positive emotions of person i at time t. These true scores are referred to, in the LST theory, as the latent states (Steyer et al., 2015). In our example, they represent the error-free positive state emotions of a person at the situation of reference where the measurement took place. In contrast, ε_{it} is an m-variate vector with the deviations of the observed scores from the latent states (true scores). These deviations are known as random measurement error. They capture the unsystematic variability of the observed scores that is not due to the person, the situation, or the person–situation interaction (Steyer et al.,

2015). The random measurement errors ε_{it} are assumed to be uncorrelated and normally distributed with means of zero and $m \times m$ diagonal covariance matrix Σ_ε.

Moreover, the true scores τ_{it} are further decomposed as follows:

$$\tau_{it} = \alpha + \Lambda_T \xi_{ir} + \Gamma_i d_{it} + \lambda_S O_{it}, \tag{3}$$

where α is an m-variate vector with the intercepts of the observed emotions, which can be interpreted as the grand means. Next, ξ_{ir} is an m-variate vector with the factor scores of the latent indicator- and situation-specific traits of the positive emotions of person i. These trait scores are assumed to represent the trait level of the positive emotions of person i at the first measurement occasion when the person was alone. The trait scores of the first measurement occasion influence all the future latent states τ_{it} with $t > 1$ (Eid et al., 2017). Next, Λ_T is just the $m \times m$ identity matrix. Note that the latent indicator-specific traits ξ_{ir} are latent variables with just one indicator. Therefore, the loadings need to be fixed to 1, otherwise the model is unidentified. Moreover, the latent trait scores are assumed to be normally distributed with a mean of zero and an $m \times m$ covariance matrix Σ_ξ. Alternatively, one can set the intercepts α to zero and estimate the means of the latent traits ξ_{ir} (as shown in Figure 2). Then, d_{it} is an l-variate vector of 0s and 1s that indicates the fixed situation of person i at time t, and Γ_i is an $m \times l$ matrix with the effects of the fixed situations on each of the indicators of person i. For example, if the fixed situations are "being alone" and "not being alone", "being alone" can be the reference situation. In this case, d_{it} is just a scalar (0 if the person was alone or 1 if the person was not) and Γ_i is an m-variate vector with the effects of "not being alone" on each of the positive emotions of person i. These coefficients indicate by how much the latent trait scores of the positive emotions increase or decrease when the person is not alone. Hence, they represent the effect of the situation. Note that Γ_i is a matrix of random slopes, which can be further modeled in the between-person equations. Lastly, O_{it} is a scalar that represents the score of the latent occasion-specific variable of person i at time t, which, in our example, is a combination of the state of positive affect at time t and the carry-over effect of states of positive affect from previous time points. The latent occasion-specific variable O_{it} at time t is related to the states of positive emotions τ_{it} at time t via the m-variate vector with the factor loadings λ_S.

Finally, the ME-TSO model acknowledges the dynamic nature of persons by assuming that the latent occasion-specific variables follow an autoregressive structure of order 1. This means that the latent occasion-specific variable at time t is regressed on the latent occasion-specific variable at time $t - 1$, that is,

$$O_{it} = \varphi_i O_{i,t-1} + \zeta_{it}, \tag{4}$$

where $O_{i,t-1}$ is a scalar that represents the score of the latent occasion-specific variable of person i at time $t - 1$; ζ_{it} is a scalar that captures the residual of the autoregressive process of person i at time t, which is referred to, in the LST theory, as the latent occasion-specific residual. This residual represents the pure state of positive affect that is only due to the situation

without the influence of the trait, the states of previous measurements, or the interaction between the person and the fixed situations. The latent occasion-specific residual ζ_{it} is assumed to be normally distributed with mean zero and variance σ_ζ^2. Finally, φ_i is the autoregressive effect of person i, which represents the individual carry-over effect between consecutive states of positive affect. In other words, φ_i is a random slope that is normally distributed with mean $E(\varphi)$ and variance σ_φ^2 (see Figure 2).

Additional advantages of extending the TSO model within the DSEM framework are that observed variables are latent person-mean centered for the analysis and that the model can handle observations that are unequally spaced over time. Firstly, DSEM uses latent centering (Asparouhov et al., 2018; McNeish & Hamaker, 2020), which means that the observed variables are centered based on their latent intraindividual means instead of the observed intraindividual means. This is better, because using latent centering implies that all the fluctuations and random error are captured in the within-level model. As a result, the within-person effects are more meaningful and interpretable in comparison with analyses when no centering or when grand mean centering is used (McNeish & Hamaker, 2020). Furthermore, latent centering avoids Nickell's bias for the autoregressive effects and Lüdtke's bias for the effects of other time-varying covariates (Asparouhov et al., 2018; McNeish & Hamaker, 2020), which can appear when observed person-mean centering is used.

Secondly, a common challenge of intensive longitudinal data is that measurements are not equally spaced over time. When this happens, the auto- and cross-regressive effects, which are parameters of key interest in dynamic models, do not have a clear meaning given that the size of these effects depends on the size of the time interval between the measurements. To handle this issue in DSEM, one can include additional missing values to approximate the measurements to be relatively equally spaced over time (Hamaker et al., 2018; McNeish & Hamaker, 2020). This technique offers results that are similar to the results obtained via continuous time models (De Haan-Rietdijk et al., 2017) and it retrieves good estimates with a percentage of missing values as large as 80% (Asparouhov et al., 2018).

Lastly, to study the person–situation interaction, the LST-RF approach (Geiser et al., 2015) proposes to regress the random slopes of the effect of the fixed situations on the trait variables at the between-level model. For the ME-TSO model, this means to regress the random slopes in Γ_i on the respective latent indicator- and situation-specific trait variables ξ_{ir}. This regression is expressed as follows given a slope γ_{ijf} of the matrix Γ_i:

$$\gamma_{ijf} = \beta_{0jf} + \beta_{1jf}\xi_{ijr} + \omega_{ijf}, \qquad (5)$$

where γ_{ijf} is the effect of the fixed situation f on the indicator j of person i, and ξ_{ijr} is the factor score of the latent indicator- and situation-specific trait variable of indicator j of person i. This regression is described by the coefficients β_{0jf} and β_{1jf}, which are the intercept and the slope, respectively. The slope β_{1jf} can be interpreted as the person–situation interaction

effect. Finally, ω_{ijf} is the residual of the regression, which is assumed to be normally distributed with mean zero and variance $\sigma_{\omega jf}^2$. This is the part of the effect of the situation of person i that cannot be explained by the trait scores of the reference situation. Furthermore, one can add additional time-invariant covariates in Equation 5 to further explain the variability of the effect of the situation on the daily observations. Note that the random slope γ_{ijf} represents the difference between the trait of the person at the f fixed situation against the trait of the person at the reference situation (i.e., $\gamma_{ijf} = \xi_{ijf} - \xi_{ijr}$). This underlying structure of the indicator- and situation-specific trait variables is shown in Figure 3.

The key element of Equation 5 is the slope β_{1jf} that represents the interaction between the persons' j-th trait with the f-th fixed situation. For example, let "feeling happy" be one of the positive emotions measured in the ambulatory assessment in which "being alone" was the reference situation and "not being alone" was the fixed situation. The slope β_{1jf} represents the interaction between the trait level of happiness during the reference situation with the effect of "not being alone" on the state happiness. In this case, $\beta_{1jf} > 0$ means that persons with higher scores of trait happiness in the reference situation are more likely to have a stronger situation effect in situations when they are not alone. Hence, being not alone implies a higher increase in state happiness, if the trait happiness of the person is also high. On the contrary, $\beta_{1jf} < 0$ means that persons with higher scores of trait happiness in the reference situation are more likely to have a weaker situation effect in situations when they are not alone.

Variance coefficients

A fundamental contribution of LST models is the variance coefficients (Steyer et al., 2015). These coefficients allow studying the psychometric properties of the instruments used in longitudinal studies. In a nutshell, they are defined as proportions of the total variance of each indicator that are explained
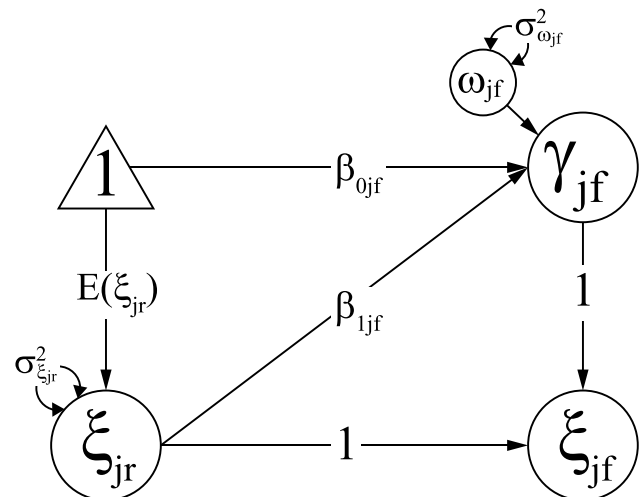
Figure 3. Path diagram representing the underlying structure of the relationship between the indicator- and situation-specific traits of the reference and the fixed situations.

by certain components of the model. Diverse variance coefficients are defined based on the complexity of the model. However, the most essential variance coefficients, which are defined for every LST model, are the consistency, the occasion-specificity, and the reliability. The consistency is the proportion of the variance of an indicator that is explained by the time-invariant sources of variability. In other words, it indicates to what extent the indicators are trait-like. In contrast, the occasion-specificity is the proportion of the variance of an indicator that is explained by the time-varying sources of variability. The occasion-specificity coefficient, thus, indicates to what extent the indicators are state-like. Lastly, the reliability encompasses both, the time-invariant and the time-varying sources of variability. To put it differently, the reliability is the proportion of the variance that is explained by the true score.

For the ME-TSO model proposed in this study, two sets of coefficients can be defined depending on whether they describe the variability across fixed situations or random situations (Geiser et al., 2015). First of all, the coefficients across fixed situations are the consistency of traits, the situation-specificity of traits, the person–situation interaction coefficient, and the unique situation effect. These coefficients are derived from the assumed underlying structure of the indicator- and situation-specific traits shown in Figure 3. The consistency of trait is defined as $[Corr(\xi_{jr}, \xi_{jf})]^2$, which is the squared correlation of the indicator- and situation-specific trait variable of the reference situation with the indicator- and situation-specific trait variable of the fixed situation f. This coefficient indicates the proportion of variance that is shared between the two indicator- and situation-specific traits. Notice that the correlation between the two indicator- and situation-specific traits ($Corr(\xi_{jr}, \xi_{jf})$) is not directly estimated in the model but it has to be computed based on other parameters of the model as shown in Equation 6 (for the mathematical derivation of these equations see the supplementary material). Next, the situation-specificity of traits is defined as $1 - [Corr(\xi_{jr}, \xi_{jf})]^2$ and represents the proportion of the variance that is unique between the two indicator- and situation-specific traits.

$$Var(\xi_{jf}) = Var(\xi_{jr}) + 2\beta_{1jf}Var(\xi_{jr}) + \beta_{1jf}^2 Var(\xi_{jr}) + Var(\omega_{jf})$$

$$Cov(\xi_{jr}, \xi_{jf}) = Var(\xi_{jr}) + \beta_{1jf}Var(\xi_{jr})$$

$$Corr(\xi_{jr}, \xi_{jf}) = \frac{Cov(\xi_{jr}, \xi_{jf})}{\sqrt{Var(\xi_{jr})Var(\xi_{jf})}}$$

$$(6)$$

Furthermore, the person–situation interaction coefficient and the unique situation effect are defined as proportions of the variance of the random effect of the situation, γ_{jf}. The total variance of γ_{jf} is defined as follows:

$$Var(\gamma_{jf}) = \beta_{1jf}^2 Var(\xi_{jr}) + Var(\omega_{jf}), \quad (7)$$

which is derived from Equation 5. Thus, the person–situation interaction coefficient is the proportion of the variance of γ_{jf} that is explained by the indicator- and situation-specific trait variable of the reference situation (i.e., $\beta_{1jf}^2 Var(\xi_{jr})/Var(\gamma_{jf})$). Therefore, it is the proportion of the variance of the situation effect that is due to the person–situation interactions. In contrast, the unique situation effect is the proportion of the variance that is not explained by the person–situation interactions (i.e., $Var(\omega_{jf})/Var(\gamma_{jf})$). This coefficient should decrease toward 0 when adding more time-invariant covariates to the model as they further explain the person–situation interaction.

Additionally, variance coefficients within fixed situations (across random situations) can also be defined. This means that we can compute the traditional variance coefficients of the TSO model (Eid et al., 2017) for each of the fixed situations. This includes the reliability (Rel), the consistency (Con), the occasion-specificity (Ospe), the predictability by trait (Pred), and the unpredictability by trait (Upred). These coefficients are usually defined for each indicator j at time t, allowing the variance coefficients to change over time.[1] However, in the present study, we adapted all these variance coefficients in such a way that they do not change over time and we defined them for each person i, for each indicator j, and for each fixed situation f. This adjustment aims to provide variance coefficients that are more meaningful for the ME-TSO model, by taking into account the emphasis on the individual and the effect of different fixed situations. Therefore, given the time series Y_{ijf} of the variable j, of person i, in the fixed situation f (with $f = r, 1, \ldots, l$), the total variance of Y_{ijf} is defined as follows[2]

$$Var(Y_{ijf}) = Var(\xi_{jf}) + \lambda_{S_j}^2 \frac{\varphi_i^2}{1 - \varphi_i^2} Var(\zeta) + \lambda_{S_j}^2 Var(\zeta) + Var(\varepsilon_j). \quad (8)$$

The rationale and derivation of this total variance is included in the supplementary material.

Once the total variance is defined, defining the variance coefficients becomes trivial as they are just proportions of the total variance. The equations for the five variance coefficients of the ME-TSO model are shown in Equations 9–13. As mentioned before, the consistency, the occasion-specificity, and the reliability are defined for every LST model. The only difference in this case is that they are defined for each indicator, each person, and each fixed situation. On the other hand, the predictability by trait and the unpredictability by trait are variance coefficients exclusively defined for TSO models. These two coefficients added together are the consistency. In the first place, the predictability by trait is the proportion of the total variance that is explained by the latent indicator- and situation-specific trait variable. It represents the proportion of the variance that is stable over time and predicted by the indicator- and situation-specific trait of the first measurement occasion.

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[1]This is the case for the TSO model even when all the parameters are assumed to be time invariant. This happens due to the autoregressive structure of the model, which makes all the variance coefficients to inevitably change over time. In particular, the reliability, the consistency, and the unpredictability by trait increase over time and tend to an upper asymptote. On the other hand, the occasion-specificity and the predictability by trait decrease over time and tend to a lower asymptote. This is further explained in the supplementary material.

[2]The total variance and the variance coefficients within fixed situations (Equations 8–13) are computed for each individual. This means that the individual estimates of φ_i need to be extracted in order to compute these coefficients.

In contrast, the unpredictability by trait is the proportion of the total variance that is explained by the previous states. To put it differently, the unpredictability by trait represents the proportion of the variance that is due to the autoregressive (carry-over) process, hence, it represents some sort of stability over time that is not explained by the indicator- and situation-specific trait of the first measurement occasion. In relation to similar reliability coefficients as the ones proposed by Fuller-Tyszkiewicz et al. (2017) and Schuurman and Hamaker (2019), the advantage of the variance coefficients proposed for the ME-TSO model is that the autoregressive structure is taken into account for its computation.

$$Con(Y_{iif}) = \frac{Var(\xi_{jf}) + \lambda_{S_j}^2 \frac{\varphi_i^2}{1-\varphi_i^2} Var(\zeta)}{Var(Y_{iif})} \quad (9)$$

$$Pred(Y_{iif}) = \frac{Var(\xi_{jf})}{Var(Y_{iif})} \quad (10)$$

$$Upred(Y_{iif}) = \frac{\lambda_{S_j}^2 \frac{\varphi_i^2}{1-\varphi_i^2} Var(\zeta)}{Var(Y_{iif})} \quad (11)$$

$$Ospe(Y_{iif}) = \frac{\lambda_{S_j}^2 Var(\zeta)}{Var(Y_{iif})} \quad (12)$$

$$Rel(Y_{iif}) = \frac{Var(\xi_{jf}) + \lambda_{S_j}^2 \frac{\varphi_i^2}{1-\varphi_i^2} Var(\zeta) + \lambda_{S_j}^2 Var(\zeta)}{Var(Y_{iif})} \quad (13)$$

Applying the ME-TSO model

In this section, we present the application and interpretation of the ME-TSO model via an empirical example. For this, we analyzed daily diary data collected in the HowNutsAreTheDutch study (Dutch: HoeGekIsNL; van der Krieke et al., 2017; van der Krieke et al., 2016). Data were collected between May 2014 and December 2018. The detailed description of the How Nuts Are The Dutch data and the design of the project are available in van der Krieke et al. (2016). For the present application, we analyzed the items used to measure positive affect, which were measured based on the circumplex model of affect (Feldman Barrett & Russell, 1988, and Yik et al., 1999, as cited in van der Krieke et al., 2016). This means that positive affect emotions are divided into two categories: Positive affect activation and positive affect deactivation. More precisely, in this empirical example, we analyzed the items of positive affect activation. Furthermore, to study the person–situation interaction, we considered two situational variables. Firstly, we considered whether something negative happened between the previous and the current measurements. Secondly, we considered whether the persons were alone or in

a social situation at the moment of measurement. These analyses are similar to the analyses presented by Geiser et al. (2015), which also studied, with different data, how daily fluctuations of positive emotions are related with the fixed situations of being alone versus being in a social situation and whether there were person–situation interaction effects.

In this analysis, we aimed to study the psychometric properties of the items of positive affect activation across different fixed situations. Furthermore, we aimed to study the person–situation interaction effects between the positive emotions and the fixed situations of interest while controlling for the lagged structure in the data. Specifically, we wanted to know whether a negative event has a negative effect on the positive affect activation emotions. Similarly, we explored whether being in a social situation leads to an increase of the items of positive affect. Furthermore, we wanted to know whether there are interaction effects such that the trait component of the positive affect emotions in the reference situation predicts the size of the effect of the fixed situations of interest. Lastly, we added optimism as a time-invariant covariate of the situation effects. Hence, optimism was added to further explain the person–situation interactions. Note that we have previously analyzed these data with the TSO model, without considering random autoregressive effects or person–situation interaction effects (Castro-Alvarez et al., 2021).

Data

The data for these analyses include the time series of positive emotions of 644[3] dutch individuals (83.9% women, mean age 39.9). Participants reported their emotions three times a day for 30 days, resulting in time series with a maximum length of 90 observations per individual. The number of observations per individual ranged from 59 to 90 with a mean of 74.9 observations per participant. The mean missingness rate for the selected sample was 16.7%.

The items related to positive affect activation were measured on a visual analogue scale (VAS) from 0 to 100. Positive affect activation was measured with the following three items: *Energetic, enthusiastic,* and *cheerful.* As mentioned before, some characteristics of the situations where the measurements took place were also reported. These variables were included in the analysis as dummy coded variables. In particular, we are interested in the situations where nothing negative happened (0) versus something negative happened (1), which we refer to as variable *event*; and in the situations when the participants were alone (0) versus when they were not alone (1), which we refer to as variable *alone*. These kind of situations are commonly studied in relation to daily fluctuations of affect (see M. C. Wichers et al., 2009; Elmer et al., 2020; Van Roekel et al., 2015; M. Wichers et al., 2010). Lastly, we also included the variable *optimism*, which was measured with the Life Orientation Test – Revised (van der Krieke et al., 2016) during the cross-sectional stage of the HowNutsAreTheDutch project.

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[3]The 644 individuals were selected out of 1396 individuals available in the data. Only individuals that responded to at least 65% (59 out of 90) of the beeps in the daily diary study were considered for the analyses. This criterion is also used within the HowNutsAreTheDutch project to provide personalized feedback to the participants van der Krieke et al. (2016). Furthermore, given that participants were able to do the daily diary multiple times, only the first daily diary of each participant was taken into account.

We included *optimism* mainly to showcase how to add additional time-invariant covariates to the model. In short, to show the possibilities of the ME-TSO model, we included a latent construct measured by three indicators (positive effect activation), a time-varying situational variable (event or alone), and a time-invariant covariate (optimism).

Analyses

We considered four models to analyze the data. Model 1 ($\mathcal{M}_1$) is the ME-TSO model with *event* as the situational dummy variable, to study the effect of a negative event on the daily fluctuations of positive affect and the possible interaction between the persons and the situations where something negative happened. Model 1b ($\mathcal{M}_{1b}$) is the same as $\mathcal{M}_1$ but with the addition of *optimism* as a time-invariant covariate, to study whether *optimism* also plays a role in explaining the person–situation interaction. Model 2 ($\mathcal{M}_2$) is the ME-TSO model with *alone* as the situational dummy variable. Note that in $\mathcal{M}_2$, "being alone" is the reference situation; hence, the model studied the effect of being in a social situation on the daily fluctuations of positive affect. Lastly, model 2b ($\mathcal{M}_{2b}$) is also equal to $\mathcal{M}_2$ but with *optimism* as a time-invariant covariate. In particular, based on Equations 2–4, $\mathcal{M}_{1b}$ can be defined by the following equations:

$$\begin{bmatrix} EG_{it} \\ EN_{it} \\ CH_{it} \end{bmatrix} = \begin{bmatrix} \xi_{EG,i1r} \\ \xi_{EN,i2r} \\ \xi_{CH,i3r} \end{bmatrix} + \begin{bmatrix} \gamma_{EG,i11} \\ \gamma_{EN,i21} \\ \gamma_{CH,i31} \end{bmatrix} EV_{it} + \begin{bmatrix} 1 \\ \lambda_{EN,S_2} \\ \lambda_{CH,S_3} \end{bmatrix} O_{PA,it}$$
$$+ \begin{bmatrix} \varepsilon_{EG,i1t} \\ \varepsilon_{EG,i2t} \\ \varepsilon_{CH,i3t} \end{bmatrix}, \tag{14}$$

$$O_{PA,it} = \varphi_i O_{PA,i,t-1} + \zeta_{PA,it}, \tag{15}$$

where EG_{it}, EN_{it}, and CH_{it} are the observations of person i at time t of the items *energetic*, *enthusiastic*, and *cheerful*, respectively; $\xi_{EG,i1r}$, $\xi_{EN,i2r}$, and $\xi_{CH,i3r}$ are the latent indicator- and situation-specific trait scores of person i for the reference situation; and $\varepsilon_{EG,i1t}$, $\varepsilon_{EN,i1t}$, and $\varepsilon_{CH,i1t}$ are the measurement errors of person i at time t. Next, EV_{it} is the score of the dummy variable that indicates whether something negative-happened for person i at time t; $\gamma_{EG,i11}$, $\gamma_{EN,i21}$, and $\gamma_{CH,i31}$ and are the effects of a negative event on the positive emotions of person i. Furthermore, $O_{PA,it}$ and $\zeta_{PA,it}$ are the latent occasion-specific score and residual of positive affect activation; and λ_{EN,S_2} and λ_{CH,S_3} are the factor loadings of the latent occasion-specific variables of positive affect. Recall that the first loading is fixed to 1 for identification purposes. The effects of the fixed situation ($\gamma_{EG,i11}$, $\gamma_{EN,i21}$, and $\gamma_{CH,i31}$) are further decomposed based on Equation 5 as follows:

$$\begin{bmatrix} \gamma_{EG,i11} \\ \gamma_{EN,i21} \\ \gamma_{CH,i31} \end{bmatrix} = \begin{bmatrix} \beta_{011} \\ \beta_{021} \\ \beta_{031} \end{bmatrix} + \begin{bmatrix} \beta_{111} & 0 & 0 \\ 0 & \beta_{121} & 0 \\ 0 & 0 & \beta_{131} \end{bmatrix} \begin{bmatrix} \xi_{EG,1r} \\ \xi_{EG,1r} \\ \xi_{EG,1r} \end{bmatrix}$$
$$+ \begin{bmatrix} \beta_{OPT,1} \\ \beta_{OPT,2} \\ \beta_{OPT,3} \end{bmatrix} OPT_i + \begin{bmatrix} \omega_{EG,i11} \\ \omega_{EN,i21} \\ \omega_{CH,i31} \end{bmatrix} \tag{16}$$

where β_{0j1} and β_{1j1} are the intercept and the slope of the j-th indicator for the situation where something negative happened. The slope represents the person–situation interaction that is the effect of the trait of the situation of reference on the situational effect of a negative event on a certain emotion (e.g., energetic). Additionally, OPT_i is the score of person i on the cross-sectional variable *optimism*, and $\beta_{OPT,j}$ is its respective effect on the j-th indicator. Lastly, $\omega_{EG,i11}$, $\omega_{EN,i21}$, and $\omega_{CH,i31}$ are the residuals reflecting the effect of a negative event on a certain emotion that remains unexplained. Estimates for each of the parameters in Equations 14–16 are included in the supplementary material.

To evaluate the relative fit of the models and to select the best fitting model, we applied the deviance information criterion (DIC). The DIC as well as other relative fit measures indicate that a model fits the data best when the DIC value is the lowest among the competing models. Note that the DICs reported for different DSEM models are not always comparable (Asparouhov et al., 2018). This is a problem especially when comparing DSEM models with several latent variables. To be comparable, the list of latent variables that are treated as parameters needs to be same. This requirement is satisfied in our analyses, given that all four tested model have the same number of latent variables.

Preliminary steps

As mentioned before, the ME-TSO model requires that multiple items measure the same construct. This is the case in the HowNutsAreTheDutch data with the items of positive affect activation (Castro-Alvarez et al., 2021). Before fitting the models, we described and visualized the raw data. For example, Figure 4 shows the time series of the items of positive affect activation of four individuals. These time series also show that the three items follow similar trends, which is expected because they are supposed to measure the same construct. Furthermore, Figure 5 shows the overall differences in the items across the situations when nothing negative happened versus something negative happened. This clearly shows that there is probably a situational effect when something negative happened. By analyzing the data with the ME-TSO model, we can study how this situational effect actually varies across persons and how it might be related to trait-like persons' characteristics.

Moreover, one has to verify that the assumptions of the model are met. In particular, the ME-TSO model assumes that the autoregressive process is stationary and that the observations are equally spaced over time. Regarding stationarity, we used the Kwiatkowski-Phillips-Schmidt-Shin test to study whether the observed time series were trend stationary (Kwiatkowski et al., 1992). This test suggested that 193 individuals had at least one nonstationary time series. However, these kinds of tests tend to be prone to commit Type I errors with short-time series ($N \leq 100$; Jönsson, 2011). For this reason, and because the results excluding the individuals with nonstationary time series
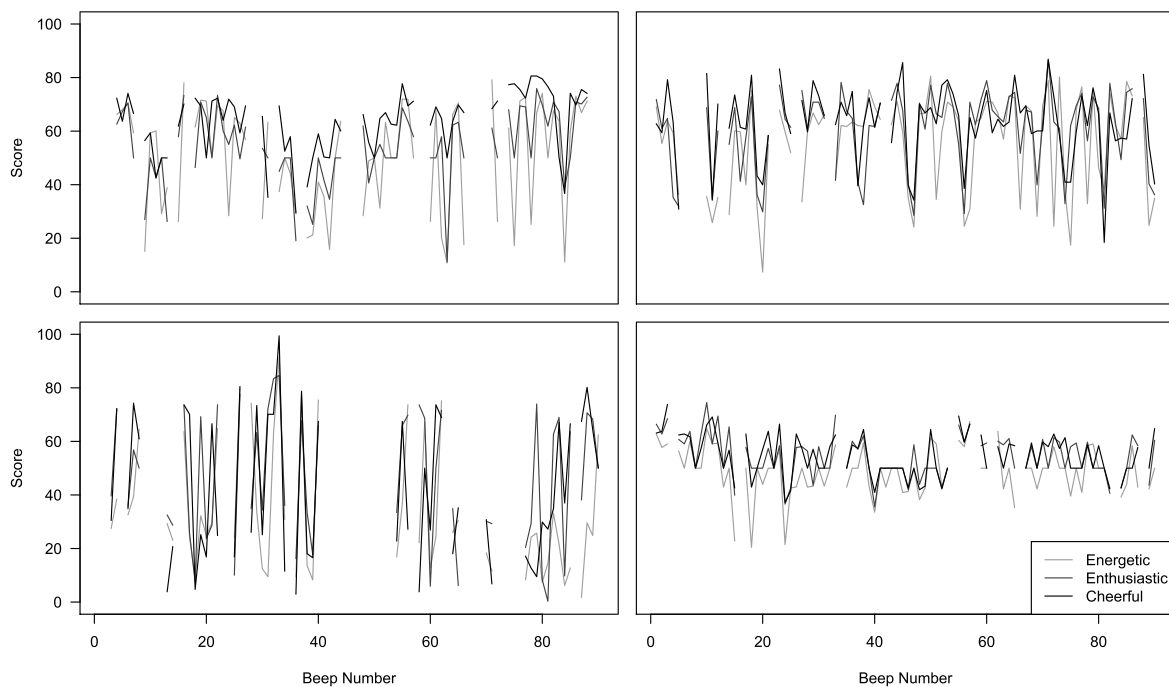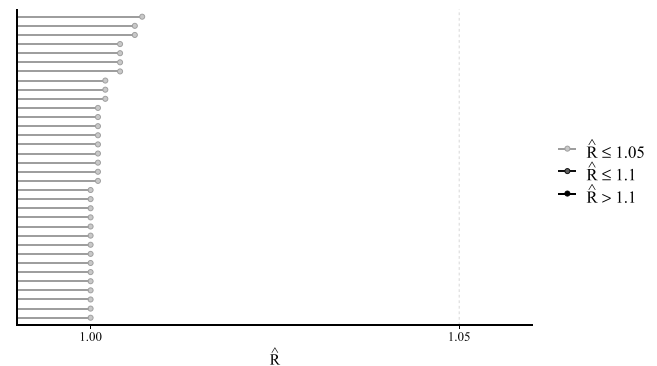
Figure 4. Time series of the positive affect activation items of four random individuals. The breaks in the time series mean that the individual did not respond at those beeps.
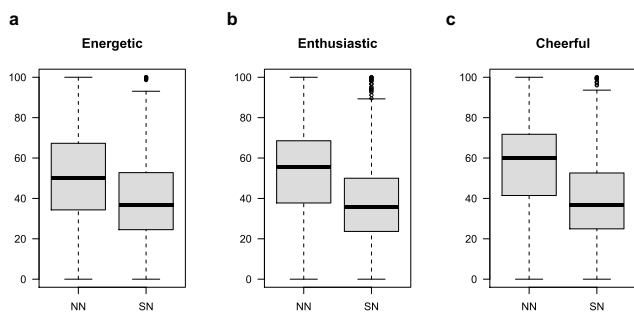
Figure 5. Boxplot of positive affect activation items by event. Overall differences in the items of positive affect activation across the variable *event*. NN = Nothing negative happened. SN = Something negative happened.

Figure 6. Gelman-Rubin statstics of $\mathcal{M}_1$. $\mathcal{M}_1$: Model 1. $\hat{R}$: Gelman-Rubin Statistic.

did not differ substantially from the results with the whole sample, we include the results with the stationary sample in the supplementary material. Another assumption is that observations are equally spaced over time. This is not the case in the HowNutsAreTheDutch data due to missing data and the overnight periods. To handle this, we approximated the data to be relatively equally spaced over time by including additional missing values. We did this automatically in Mplus with the TINTERVAL command[4] (Muthén & Muthén, 2017).

Finally, as the ME-TSO model is implemented within the Bayesian framework, it is extremely important to verify that the posterior sampling algorithm converged as expected. The convergence of Bayesian models is usually checked via the Gelman-Rubin Statistic ($\hat{R}$; Gelman & Rubin, 1992) and diagnostic plots such as traceplots and autocorrelation plots.

Figure 6 shows the estimated $\hat{R}$ statistics of $\mathcal{M}_1$, which suggests that the sampling procedure converged. The other tested models also seemed to have converged according to this criterion (See supplementary material).

Results

In this empirical example, we disentangled the trait and the state components of the emotions of positive affect activation and we studied how the psychological dynamics of positive mood are influenced by the situation and the person–situation interaction. The results of the tested model are presented in Tables 1–2. These tables include the estimates and the credibility intervals of the key parameters of the ME-TSO model. Also, the number of free parameters, the DIC, and estimated number of parameters (pD) are reported at the bottom of Tables 1–2. From this,

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[4]All the code to run the models is available in the git repository https://github.com/secastroal/ME-TSO.

Table 1. Unstandardized estimates of the key parameters of the models using the situation variable event.

Parameter	$\mathcal{M}_1$ Est. [95% C.I.]	$\mathcal{M}_{1b}$ Est. [95% C.I.]
	Between-level	
Eg-Ev Interaction Effect β_{111}	−0.19 [−0.25, −0.13]	−0.19 [−0.26, −0.10]
En-Ev Interaction Effect β_{121}	−0.20 [−0.26, −0.13]	−0.21 [−0.26, −0.14]
Ch-Ev Interaction Effect β_{131}	−0.22 [−0.29, −0.16]	−0.24 [−0.31, −0.17]
Opt-Eg-Ev Interaction Effect $\beta_{OPT,1}$	–	−0.02 [−0.26, 0.21]
Opt-En-Ev Interaction Effect $\beta_{OPT,2}$	–	0.04 [−0.19, 0.29]
Opt-Ch-Ev Interaction Effect $\beta_{OPT,3}$	–	0.04 [−0.20, 0.29]
AR Effect Mean $E(\varphi)$	0.32 [0.30, 0.34]	0.32 [0.30, 0.34]
Eg-Ev Effect Residual Variance $Var(\omega_{EG,11})$	23.79 [15.05, 34.05]	23.92 [14.76, 34.28]
Et-Ev Effect Residual Variance $Var(\omega_{EN,21})$	41.63 [31.06, 54.34]	41.98 [31.74, 54.52]
Ch-Ev Effect Residual Variance $Var(\omega_{CH,31})$	46.16 [34.97, 59.47]	46.19 [35.00, 59.56]
AR Effect Variance $Var(\varphi)$	0.033 [0.028, 0.039]	0.033 [0.028, 0.039]
	Model Fit Information	
Number of Free Parameters	34	43
DIC	1823224.25	1,825,196.44
pD	141759.28	141,883.55

$\mathcal{M}_1$: Model 1, $\mathcal{M}_{1b}$: Model 1b, Est.: Unstandardized estimate, C.I.: Credibility interval, Eg: Energetic, En: Enthusiastic, Ch: Cheerful, Ev: Event, DIC: Deviance information criterion, pD: Estimated number of parameters.

Table 2. Unstandardized estimates of the key parameters of the models using the situation variable alone.

Parameter	$\mathcal{M}_2$ Est. [95% C.I.]	$\mathcal{M}_{2b}$ Est. [95% C.I.]
	Between-level	
Eg-Al Interaction Effect β_{111}	−0.08 [−0.12, −0.04]	−0.04 [−0.10, −0.01]
En-Al Interaction Effect β_{121}	−0.10 [−0.13, −0.07]	−0.08 [−0.12, −0.04]
Ch-Al Interaction Effect β_{131}	−0.09, [−0.12, −0.06]	−0.07 [−0.11, −0.03]
Opt-Eg-Al Interaction Effect $\beta_{OPT,1}$	–	−0.16 [−0.31, −0.01]
Opt-En-Al Interaction Effect $\beta_{OPT,2}$	–	−0.13 [−0.27, 0.00]
Opt-Ch-Al Interaction Effect $\beta_{OPT,3}$	–	−0.10 [−0.23, 0.03]
AR Effect Mean $E(\varphi)$	0.33 [0.31, 0.35]	0.33 [0.31, 0.35]
Eg-Al Effect Residual Variance $Var(\omega_{EG,11})$	18.63 [14.59, 23.11]	18.30 [14.25, 23.08]
Et-Al Effect Residual Variance $Var(\omega_{EN,21})$	13.74 [10.62, 17.53]	13.58 [10.31, 17.36]
Ch-Al Effect Residual Variance $Var(\omega_{CH,31})$	10.42 [7.59, 13.74]	10.44 [7.43, 13.87]
AR Effect Variance $Var(\varphi)$	0.032 [0.027, 0.039]	0.033 [0.027, 0.039]
	Model Fit Information	
Number of Free Parameters	34	43
DIC	1932395.64	1,934,237.58
pD	150001.81	149,947.33

$\mathcal{M}_2$: Model 2, $\mathcal{M}_{2b}$: Model 2b, Est.: Unstandardized estimate, C.I.: Credibility interval, Eg: Energetic, En: Enthusiastic, Ch: Cheerful, Al: Alone, DIC: Deviance information criterion, pD: Estimated number of parameters.

we can observe that $\mathcal{M}_1$ and $\mathcal{M}_{1b}$ are better at explaining the daily variability of the positive emotions than the models $\mathcal{M}_2$ and $\mathcal{M}_{2b}$. This means that the occurrence of a negative event is more likely to influence the daily fluctuations of positive mood than being alone.

In relation to *optimism*, the analyses showed that adding this variable does not substantially improve the fit of $\mathcal{M}_1$ nor $\mathcal{M}_2$. Additional evidence against $\mathcal{M}_{1b}$ and $\mathcal{M}_{2b}$ is that the amount of unexplained variance of the effects of the situation at the between-level (ω_{jf}) did not decrease (see Tables 1–2). Therefore, a person's *optimism* typically does not interact with the situation effect (i.e., something negative happening or not being alone) on the daily emotions of the persons.

Additionally, one can look at some key parameters of the model such as the random autoregressive effect φ_i and the interaction effects β_{1jf}. Firstly, the estimated mean autoregressive effect ($E(\varphi)$) in $\mathcal{M}_1$ and $\mathcal{M}_2$ evidenced that there is on average a moderate carry-over effect on the states of positive affect activation. Nonetheless, there are important differences in the

lagged relationships across individuals given the estimated variance of the random autoregressive effect ($Var(\varphi) = 0.033$). In other words, there are participants that show little to no carry-over effects on positive affect activation as well as participants that show strong carry-over effects on their positive affect dynamics. Secondly, $\mathcal{M}_1$ showed that there are person–situation interactions between the situational variable *event* and the trait components of each positive emotion ($\beta_{111} = -0.19$, $\beta_{121} = -0.20$, $\beta_{131} = -0.22$). This means that the trait level of the positive affect emotions interacts with the effect of a negative event on the daily emotions of the participants. Therefore, the lower the trait positive emotion of a person, the stronger the negative effect of a negative event on the daily emotions. In other words, the daily emotions of an individual that is not too enthusiastic (trait enthusiastic) will decrease more when something negative happen, than the daily emotions of an individual that tends to be enthusiastic. On the other hand, $\mathcal{M}_2$ also showed that there are person–situation interactions between the situation variable *alone* and the trait components of each positive

emotion ($\beta_{111} = -0.08$, $\beta_{121} = -0.10$, $\beta_{131} = -0.09$). Therefore, the lower the trait positive emotion of a person, the stronger the positive effect of not being alone on the daily emotions. To put it differently, being in a social situation has a more positive impact on individuals that tend to have low levels of positive emotions when they are alone than on individuals that tend to have high levels of positive emotions. However, the size of these interactions was lower in comparison to the size of the interactions in $\mathcal{M}_1$. Moreover, while the interaction effects in $\mathcal{M}_2$ might be statistically significant, they are not necessarily practically significant.

Finally, we report the variance coefficients of $\mathcal{M}_1$. These coefficients are the added value of the ME-TSO model when compared with more traditional and simpler methods for intensive longitudinal data. In brief, these variance coefficients indicate the strength of the person–situation interaction and allow studying the psychometric properties of the items according to the LST theory. Firstly, the coefficients across fixed situations of the ME-TSO quantify the strength of the person–situation interaction, which, to the best of our knowledge, is not possible in other approaches for intensive longitudinal data. Secondly, the variance coefficients within fixed situations are used to study the psychometric properties of the items and to determine to what extent the items are trait- or state-like. Alternatively, this could be done with for example, the between- and the within-reliabilities (Schuurman & Hamaker, 2019) and the intraclass-correlation (Houben et al., 2020). However, these indices might come short when compared with the variance coefficients within fixed situations of the ME-TSO model as they do not account for the autoregressive structure of the data. In what follows, we present and interpret the estimated variance coefficients of $\mathcal{M}_1$.

Table 3 shows the estimated variance coefficients across fixed situations. Firstly, the consistency of traits of *energetic* (0.8) was the highest across the three items, which means that the interindividual differences in *energetic* tend to be consistent across the two situations. Secondly, the person–situation interaction coefficient varied between 13% and 19% across the three items (see the fourth column in Table 3). This means that an important part of the variability of the situation effects is due to the person–situation interaction effects. To put it differently, the effect of the situation not only depends on the situation happening but also on the trait level of the positive emotions of the individuals.

Furthermore, in the ME-TSO model, one can also estimate the variance coefficients within fixed situations.[5] Note that these variance coefficients are estimated for each item, and they also vary across individuals. Therefore, in Table 4, we present the average and the standard deviation of the estimated variance coefficients for each item and each fixed situation. In relation to

Table 4. Variance coefficients within fixed situations.

	Items		
	Energetic	Enthusiastic	Cheerful
Variance Coefficient	M (SD)	M (SD)	M (SD)
	Nothing Negative Happened		
Reliability	0.70 (0.02)	0.83 (0.01)	0.79 (0.01)
Consistency	0.38 (0.03)	0.42 (0.04)	0.43 (0.03)
Occasion-Specificity	0.32 (0.02)	0.41 (0.03)	0.36 (0.02)
Predictability by Trait	0.33 (0.02)	0.36 (0.02)	0.37 (0.02)
Unpredictability by Trait	0.05 (0.05)	0.06 (0.06)	0.06 (0.05)
	Something Negative Happened		
Reliability	0.67 (0.02)	0.83 (0.01)	0.77 (0.01)
Consistency	0.33 (0.03)	0.4 (0.04)	0.4 (0.03)
Occasion-Specificity	0.34 (0.02)	0.43 (0.03)	0.37 (0.02)
Predictability by Trait	0.28 (0.01)	0.34 (0.02)	0.34 (0.02)
Unpredictability by Trait	0.05 (0.05)	0.06 (0.06)	0.06 (0.05)

M: Mean, SD: Standard deviation.

the reliability of the items, the item *enthusiastic* was on average the most reliable item on both fixed situations ($M = 0.83, SD = 0.01$). Moreover, the items *energetic* and *cheerful* seem to be slightly less reliable in the situations where something negative happened. In general, when considering the consistency and the occasion-specificity, the three items seem to be on average as trait-like as they are state-like in both fixed situations because the average consistencies and occasion-specificities tend to be practically equal. However, the items *energetic* and *cheerful* seem to be more trait-like in the situations where nothing negative happened. For example, the difference between the mean consistency and mean occasion-specificity of *energetic* when nothing negative happened is 0.06, while when something negative happened it is 0.01. Lastly, the consistency is divided into the predictability by trait and the unpredictability by trait. On the one hand, the mean predictability by trait of the items *enthusiastic* and *cheerful* were very similar in both fixed situations. In contrast, the mean predictability by trait of *energetic* was lower in the situations when something negative happened (0.28) in comparison with the situations when nothing negative happened (0.33). This means that the trait of *energetic* in the first measurement occasion when nothing negative happened has a larger influence on future situations than the trait of *energetic* in the first measurement occasion when something negative happened. On the other hand, the average unpredictability by trait of all items across fixed situations was between 5% and 6%. This coefficient also showed the highest variability across persons (SD between 0.05 and 0.06). This means that for some individuals the amount of total variance in their daily positive emotions that is due to the autoregressive process or carry-over effects can be as large as 15%.

Discussion

The ME-TSO model presented in this study aims to be an additional tool to model psychological dynamics. The model integrates the multilevel TSO (Castro-Alvarez et al., 2021), the LST-RF approach (Geiser et al., 2015), and the DSEM framework (Asparouhov et al., 2018). In general, the ME-TSO model allows studying the carry-over effects of psychological constructs, the person–situation interaction effects, and the psychometric

Table 3. Variance coefficients across fixed situations.

Item	Consistency of Traits	Specificity of Traits	Person-Situation Interaction Coefficient	Unique Situation Effect
Energetic	0.80	0.20	0.19	0.81
Enthusiastic	0.70	0.30	0.13	0.87
Cheerful	0.66	0.34	0.16	0.84

[5]In order to compute these variance coefficients, we extracted the estimates of the autoregresssive effects per person by using the FSCORES command in Mplus.

properties of the items per individual across fixed situations. Moreover, as it is implemented within the DSEM framework, it can be extended by allowing other parameters (i.e., factor loadings and residual variances) to vary randomly across persons or by including additional within- or between-covariates.

We illustrated how to use the model by means of the empirical example. The results showed that (a) the items of positive affect activation are relatively as state-like as they are trait-like, (b) there are carry-over effects present in the states of positive affect activation, which vary across individuals, (c) the effects of situations when something negative happened better explained the variability of the dynamics of positive affect activation than the effects of the situations when the participants were not alone, and (d) the situations when something negative happened seemed to interact with the trait level of the positive emotions of the individuals. Note that we have previously analyzed these data with the multilevel TSO model (Castro-Alvarez et al., 2021), where the parameters are fixed for the sample and thus heterogeneity between persons could not be taken into account. The analyses in this study, however, show that variability across persons is non-negligible. Moreover, Geiser et al. (2015) also studied the person–situation interaction effect between the situation *not being alone* and the emotions *happy, energetic*, and *cheerful* with different data. Their results are comparable to our results of $\mathcal{M}_2$, for example, in both studies the interaction effect between trait *energetic* and the situation was − 0.08. However, while in Geiser et al. (2015) this effect was not significant, in our example it seems to be statistically different from 0. This could be partially explained by the fact that our sample size was much larger than the one used by Geiser et al. (2015). Nevertheless, the size of the effect is what really matters, and an interaction effect of − 0.08 does not seem practically significant.

The variance coefficients per individual are key results of the proposed model. These variance coefficients allow studying the psychometric properties of the scales used in intensive longitudinal data by estimating the reliability of each item per individual. The reliabilities per person can be useful to evaluate the factor structure of each person, as suggested by Fuller-Tyszkiewicz et al. (2017). If the reliability of a person is too low, it might be an indication that the assumed factor structure does not fit this person. Hence, a different factor structure might be preferred for these cases. Additionally, the *consistency* and the *occasion-specificity* of the ME-TSO model also allow studying to what extent the variance of an item is due to stable or variable sources of variability per person. Thus, in our empirical example, we could determine whether a positive emotion was more trait-like or state-like for each individual. Similar coefficients at the individual level have been proposed previously (e.g., Fuller-Tyszkiewicz et al., 2017; Hu et al., 2016; Schuurman & Hamaker, 2019). However, the added value of the coefficients proposed within the ME-TSO model is that they also take into account the autoregressive structure of the psychological dynamics. In particular, with the *unpredictability by trait*, researchers can study to what extent the carry-over effects explain the overall variability of an item per person.

As with any model, the ME-TSO model has some limitations. First of all, one of the assumptions is that the autoregressive process is stationary, which can be difficult to test given that this process is unobserved in the ME-TSO model. For example, in the empirical example, we tested whether the observed time series were trend stationary. Yet, the stationarity of the observed time series does not necessarily imply that the latent autoregressive process is also stationary or vice versa. Future research can study how to improve the stationarity tests for the ME-TSO model and similar dynamic factor models (Song & Ferrer, 2012). Secondly and related to the previous point, the ME-TSO model assumes that longitudinal measurement invariance holds for all the parameters. This means that the factor structure as well as the size of the autoregressive effect does not change over time. Yet, this might not be a realistic assumption. For example, it might be the case that persons transition between different measurement models across time (Vogelsmeier et al., 2019) or that the time dependencies (autoregressive effects) change over time (Bringmann et al., 2017). Thirdly, the model also assumes that configural invariance of the within-level factor model holds. This means that the within-level factor structure is the same for all individuals. Even if the factor loadings and the residual variances are allowed to randomly vary across individuals, there might still be persons for whom the assumed factor structure is not adequate. This drawback can be overcome by, for example, allowing the random measurement variances to correlate, as suggested in the multilevel heterogeneous factor analysis model (Pan et al., 2020). Lastly, in our application of the model we used the default prior distributions available in Mplus. However, it has been shown that the default priors can lead to biased estimates under certain circumstances with latent growth models (Smid et al., 2020). Hence, in the meantime, we recommend practitioners to perform sensitivity analyses when using the ME-TSO model. Alternatively, simulation studies would be required to further investigate the impact of the priors on the estimation of the ME-TSO model.

To conclude, in the present article we presented the ME-TSO model. With this model, researchers can (a) account for the measurement error and study the psychometric properties of the items used in intensive longitudinal data, (b) estimate person–situation interaction effects, and (c) analyze the psychological dynamics of the constructs of interest per individual. We illustrated how to interpret the model with empirical data, and we provide the code to fit the model in the git repository https://github.com/secastroal/ME-TSO. With the ME-TSO model, we provided a flexible statistical tool, which can be useful to answer some of the research questions that are studied in intensive longitudinal research. We hope that this approach contributes to a better understanding of psychological dynamics. Furthermore, we expect this approach to serve as inspiration for future research to keep developing the statistical methods used to analyze intensive longitudinal data.

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